machines

MDPI

Editorial

Sustainable Manufacturing and Green Processing Methods, 2nd Edition

Ali Khalfallah [1,*], Carlos Leitão [1] and Elango Natarajan [2]

[1] CEMMPRE, Department of Mechanical Engineering, University of Coimbra, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal
[2] Faculty of Engineering, Technology and Built Environment, UCSI University, Kuala Lumpur 56000, Malaysia
* Correspondence: ali.khalfallah@dem.uc.pt; Tel.: +351-239-790-700

1. Introduction

Manufacturing systems face increasing pressure to reduce energy use, material consumption, waste generation, and environmental emissions while maintaining product quality, productivity, and economic viability. These requirements concern the entire production chain, from material selection and process planning to machining, equipment maintenance, and end-of-life management. Sustainable manufacturing should therefore be understood as a combination of technical, environmental, and organisational decisions made throughout the product life cycle [1,2].

Material processing is central to this transition because it often involves substantial energy consumption, cutting fluids, tool wear, material loss, and process-related emissions. Conventional approaches based mainly on production rate and dimensional accuracy may overlook the environmental consequences of process selection. Current research increasingly considers resource use, waste prevention, equipment durability, and process control alongside conventional measures such as cutting force, surface integrity, production time, and cost [3].

Green processing methods address these concerns through several complementary approaches. Minimum quantity lubrication can reduce dependence on conventional flood cooling [4,5]. Vibration-assisted machining can modify tool–workpiece contact and reduce the mechanical demands of cutting difficult materials [6,7]. Predictive models can limit unnecessary experiments and support the selection of processing conditions that reduce rejects and material loss. Computational simulations can identify degradation mechanisms before costly physical damage occurs. At the production-system level, structured management methods can reduce waiting time, rework, excess inventory, and inefficient resource allocation [8].

Artificial intelligence has also become relevant to sustainable manufacturing [9]. Traditional machine learning is commonly applied to prediction, classification, monitoring, and process control [10], whereas generative artificial intelligence can assist design creation, synthetic data production, scenario analysis, and knowledge-based decision-making [11,12]. Their suitability depends on the task, available data, computational requirements, expected environmental outcome, and level of human oversight.

Following the first edition of the Special Issue "Sustainable Manufacturing and Green Processing Methods" [13], this second edition continues the examination of manufacturing methods that combine technical performance with lower resource consumption and reduced environmental burdens. Its scope includes energy-efficient processing, waste prevention, recycling, cleaner production, environmental assessment, circular manufacturing, and process planning for improved resource use [14,15].

Check for updates

Received: 7 September 2026
Accepted: 15 September 2026
Published: 16 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

This Special Issue contains six contributions covering minimum quantity lubrication, ultrasonic vibration-assisted machining, predictive modelling of polymer machining, sediment erosion in hydraulic turbines, Lean implementation in custom shipbuilding, and the comparative application of generative artificial intelligence and traditional machine learning in sustainable manufacturing. Although these studies address different materials, processes, and industrial sectors, they share a common objective: improving the use of manufacturing resources through better understanding, prediction, control, and life-cycle assessment.

The contributions can be organised into four thematic groups: (i) resource-conscious machining of difficult materials; (ii) computational prediction for process quality and equipment durability; (iii) sustainable production management in custom manufacturing; and (iv) artificial intelligence methods for energy-efficient and circular manufacturing.

2. Overview and Analysis of the Contributions

2.1. Resource-Conscious Machining of Difficult Materials

Machining high-performance alloys poses a persistent environmental and technical challenge. These materials are used because of their mechanical strength, corrosion resistance, and thermal stability, but the same properties can increase cutting forces, heat generation, tool wear, and lubricant demand. Two papers in this Special Issue examine methods intended to reduce these difficulties while preserving surface quality.

2.1.1. Effect of Nozzle Parameters and Spindle Speed on the Oil Mist Penetration Mechanism in MQL High-Speed Milling of a GH4169 Alloy

Mei et al. [16] investigated oil-mist penetration during minimum quantity lubrication in the high-speed milling of GH4169. The authors develop and experimentally validate a semi-empirical model relating penetration efficiency to spindle speed, nozzle orientation, nozzle angle, and nozzle distance. Model predictions showed relative deviations below 6%. Spindle speed had the greatest effect, followed by nozzle orientation, angle, and distance. The selected parameter combination produced a surface roughness of 0.17 μm and a milling force of 24.27 N. Compared with the least favourable tested condition, surface roughness decreased by 85.32% and milling force by 53.52%. The study provides a physical basis for selecting MQL delivery parameters rather than treating them as independent empirical variables.

2.1.2. Comparative Analysis of Vibration Axis Effects on Ultrasonic Vibration-Assisted Machining of Inconel 718

Namlu and Kılıç [17] compared conventional machining with three ultrasonic vibration-assisted machining modes for Inconel 718: longitudinal, feed-direction, and combined longitudinal–feed vibration. The combined mode produced the best results because intermittent tool–workpiece contact reduced mechanical loading during cutting. Relative to conventional machining, this configuration decreased cutting forces by up to 43% and areal surface roughness by 37%. It also produced more uniform surface topographies, reduced burr formation, and increased subsurface microhardness through the surface-hammering effect. These findings indicate that vibration direction strongly affects cutting behaviour and surface integrity. The combined vibration mode may reduce tool loading and the need for secondary finishing, although its effects on energy consumption, tool life, and fatigue performance require further study.

Together, these contributions show that resource-conscious machining depends on controlling the physical conditions at the cutting interface. Lubricant delivery, vibration direction, intermittent contact, and surface formation must therefore be considered as connected aspects of machining performance.

https://doi.org/10.3390/machines14091049

2.2. Computational Prediction for Process Quality and Equipment Durability

Computational methods can reduce the number of experiments required during process development and identify failure-prone regions before production or maintenance decisions are made. Two contributions apply predictive methods to surface quality in polymer machining and sediment erosion in hydraulic turbines.

2.2.1. Ensemble Learning-Based Metamodel for Enhanced Surface Roughness Prediction in Polymeric Machining

Natarajan et al. [18] proposed a two-stage ensemble model for predicting surface roughness during the machining of polyoxymethylene, polytetrafluoroethylene, polyether ether ketone, and a PEEK composite reinforced with multi-walled carbon nanotubes. The method first classifies observations into machining regimes and then predicts surface roughness within each regime. Cutting speed, feed rate, and depth of cut are used as input variables. Logistic regression and XGBoost are assessed for classification, while support vector regression and XGBoost are tested for regression. Cross-validation and parameter tuning are used to assess model performance. The XGBoost regressor achieved coefficients of determination above 90% for all examined materials. The proposed structure addresses the difficulties associated with small and noisy machining datasets and may reduce trial machining, rejected components, and unnecessary finishing operations.

2.2.2. Lagrangian Simulation of Sediment Erosion in Francis Turbines Using a Computational Tool in Python Coupled with OpenFOAM

Narváez et al. [19] developed a computational method for predicting sediment erosion in Francis turbines. The method combines a Python tool, the Oka erosion model, Lagrangian particle tracking, and computational fluid dynamics in OpenFOAM. A reduced-domain approach excludes the spiral casing while reproducing its particle-induced swirl, thereby decreasing meshing complexity and computational cost. Application to a full-scale turbine at the San Francisco hydropower plant in Ecuador showed that erosion was concentrated near runner-blade trailing edges and on the pressure sides of guide vanes. Most particle impacts occurred at near-normal angles and velocities of 6 to 9 m/s, while infrequent high-velocity impacts caused much greater material loss. The method can inform inspection planning, local geometric modifications, material selection, and protective-coating strategies for turbines operating under sediment-laden conditions.

These studies illustrate two uses of computational prediction. The first concerns product quality during machining, while the second concerns damage to energy-sector equipment. In both cases, the practical benefit depends on whether the predictions lead to fewer experiments, lower material consumption, reduced downtime, or longer component life.

2.3. Sustainable Production Management in Custom Manufacturing

Sustainable manufacturing also concerns the organisation of production. In low-volume and custom manufacturing, inefficient coordination, waiting, rework, and excess inventory can cause substantial material and energy losses.

Lean

Kunkera et al. [20] propose a Lean process-management implementation model for European shipbuilding, where production involves complex products, low volumes, individual customer requirements, and coordination among numerous participants. Based on archival information, professional experience, and interviews with representatives of a European shipyard, the model addresses the risk of incomplete Lean implementation in custom production. It permits production improvements to occur during the implementa-

tion period and is designed to remain applicable across different organisational structures. The study extends waste reduction beyond discarded material to include waiting, rework, excess inventory, unnecessary movement, and inefficient information flow. Although developed for shipbuilding, the model may apply to other complex, low-volume industries. Further implementation studies are needed to assess its effects on production time, material waste, energy consumption, costs, and employee participation.

2.4. Artificial Intelligence for Energy-Efficient and Circular Manufacturing

Artificial intelligence methods are increasingly applied to process monitoring, energy management, waste reduction, predictive maintenance, design, and production planning. Their use should account for the energy and material demands of computation, as well as data quality, interpretability, governance, and human responsibility.

Rojek and Mikołajewski [21] reviewed generative artificial intelligence and traditional machine learning in relation to energy-efficient and circular manufacturing within Industry 5.0. It proposes a life-cycle-based framework for comparing both approaches across manufacturing stages and sustainability objectives. Traditional machine learning is considered primarily in relation to prediction, classification, process control, energy forecasting, and predictive maintenance. Generative artificial intelligence is examined in connection with design generation, synthetic data, production scenarios, and knowledge-supported decision-making. The review considers how these methods may contribute to lower energy consumption, reduced material waste, and circular resource use. It also addresses their data requirements, computational demands, interpretability, governance, and human involvement. The framework provides a basis for selecting a method according to the manufacturing task, available data, life-cycle stage, and expected environmental outcome.

3. Research Trends and Scientific Challenges

The six contributions identify four main directions in sustainable manufacturing. First, the studies on minimum quantity lubrication and ultrasonic vibration-assisted machining examine process mechanisms at the cutting interface [22,23]. They show that lubricant delivery, vibration direction, intermittent contact, and cutting conditions directly affect forces, surface quality, and material removal.

Second, computational methods are increasingly used to support process planning, quality prediction, and equipment maintenance [24,25]. The contributions apply semi-empirical modelling, ensemble learning, particle tracking, and computational fluid dynamics to predict machining performance and erosion damage. These methods can reduce experimental effort, but their reliability depends on data quality, validation, uncertainty assessment, and applicability beyond the original cases.

Third, sustainability now extends from individual manufacturing operations to equipment durability and production management [26,27]. The turbine-erosion study addresses service life and maintenance, while the shipbuilding study considers organisational sources of waste in custom production.

Fourth, the review of generative artificial intelligence and traditional machine learning places computational methods within a life-cycle and Industry 5.0 context [12,28]. Method selection should consider not only predictive performance but also energy demand, data requirements, interpretability, human responsibility, and circular resource use.

A remaining challenge is the direct assessment of environmental performance. Reductions in cutting force, surface roughness, lubricant use, processing time, or prediction error are relevant indicators, but they do not provide a complete assessment. Future studies should also measure energy consumption, material loss, tool life, emissions, waste generation, component durability, and the computational burden of artificial intelligence systems.

https://doi.org/10.3390/machines14091049

Common system boundaries and reporting procedures would permit more reliable comparisons among manufacturing methods [29].

4. Industrial Implications and Future Implementation

The contributions have several possible industrial applications. The MQL study provides guidance for selecting nozzle and spindle conditions in high-speed milling. The ultrasonic machining study identifies a vibration configuration that reduces cutting forces and improves surface quality. The polymer-machining model can support process planning, while the turbine-erosion method can inform inspection, maintenance, and coating selection. The shipbuilding model provides a structured approach to introducing Lean methods in custom production.

The review article adds a life-cycle framework for selecting between generative artificial intelligence and traditional machine learning. Traditional machine learning may be preferable for defined prediction, classification, monitoring, and control tasks. Generative artificial intelligence may be more suitable for design generation, synthetic data production, knowledge retrieval, and the assessment of alternative production scenarios. A combined approach may be appropriate in some applications, provided that its computational cost, data requirements, interpretability, and governance are assessed.

Industrial adoption requires validation under extended operating conditions. Future studies should consider process reliability, equipment cost, maintenance, operator safety, compatibility with existing systems, data security, and human oversight. Environmental benefits should be measured rather than inferred solely from technical improvements [30].

Research should therefore connect process performance with energy use, material consumption, tool life, waste generation, maintenance intervals, computational demand, and production cost. Such evidence would allow manufacturers to determine whether the proposed methods provide lasting technical, environmental, and economic benefits [31].

5. Conclusions

The second edition of the Special Issue "Sustainable Manufacturing and Green Processing Methods" brings together six contributions addressing machining, predictive modelling, equipment durability, production management, and artificial intelligence methods for sustainable manufacturing. The collection shows that sustainable manufacturing involves more than replacing a conventional process with an alternative described as green. It requires careful examination of process mechanisms, resource flows, product quality, equipment life, computational demand, and organisational practice.

The machining studies demonstrate the importance of controlling lubricant delivery and tool–workpiece interaction when processing nickel-based alloys. The modelling studies show how computational methods can assist surface-quality prediction and erosion-damage assessment. The shipbuilding study draws attention to organisational waste and the difficulties of applying production-management methods in custom manufacturing. The review article provides a life-cycle basis for comparing generative artificial intelligence and traditional machine learning in energy-efficient and circular manufacturing.

Taken together, the six contributions indicate that progress in sustainable manufacturing depends on reliable measurement, suitable assessment boundaries, and careful selection of technical and computational methods. Future research should combine process performance with direct environmental and economic measures, test proposed methods under industrial conditions, account for the energy and material costs of digital systems, and report their limitations explicitly.

As Editors, we thank all authors for their contributions to this Special Issue and the reviewers for the time and care devoted to manuscript assessment. We also thank the edito-

rial team of *Machines* for their assistance throughout the review and publication process. We hope that this collection will support further research, next edition on manufacturing methods that reduce resource consumption and waste while maintaining the quality, reliability, and affordability required in industrial production.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Leal Filho, W.; Aina, Y.A.; Gatto, A.; Rampasso, I.S.; Sigahi, T.F.A.C.; Anholon, R.; Bella, R.L.F.; Quelhas, O.L.G.; de Vasconcelos, C.R.P.; Luetz, J.M. Greening the Factory Floor and Reducing the Climate Impact of the Manufacturing Sector. *Discov. Sustain.* **2025**, *6*, 1204. [CrossRef]
2. Callychurn, D.S.; Hurreeram, D.K. Redefining Sustainability and Sustainable Manufacturing in the New Age. *Discov. Sustain.* **2026**, *7*, 432. [CrossRef]
3. Yang, Q.; Ming, W. Review: Application of Green Manufacturing Processes in Precision Machining of Automotive Components. *Green. Manuf. Open* **2025**, *3*, 2. [CrossRef]
4. Sravan Metla, S.; Chi-Huang, H.; Stachiv, I.; Jeng, Y.R. Opportunities and Challenges of Minimum Quantity Lubrication as Pathways to Sustainable Manufacturing. *Results Eng.* **2025**, *28*, 108272. [CrossRef]
5. Yan, Y.; Liang, Y.; Liu, J.; Zhang, Y.; Zhang, Z. A Review of Enhancement Technologies for Minimum Quantity Lubrication Applied in Sustainable Machining. *Mach. Sci. Technol.* **2026**, *30*, 167–211. [CrossRef]
6. Khan, A.; Wang, X.; Zhao, B.; Ding, W.; Jamil, M.; Khan, A.M.; Ali, S.H.; Hussain, S.; Zhang, J.; Das, R. Ultrasonic Vibration-Assisted Cutting of Titanium Alloys: A State-of-the-Art Review. *Chin. J. Aeronaut.* **2025**, *38*, 103078. [CrossRef]
7. Liu, X.; Xiong, Y.; Yang, Q. Ultrasonic Vibration-Assisted Machining Particle-Reinforced Al-Based Metal Matrix Composites—A Review. *Metals* **2025**, *15*, 470. [CrossRef]
8. Luo, T.M.; Zhang, J.; Deng, C.J.; Luo, D.-X.; Tao, G.-B.; Cao, H.-J. Green Machining Technology and Application Driven by Digital Intelligence: A Review. *Adv. Manuf.* **2026**, *14*, 43–102. [CrossRef]
9. Kumar, V.V.; Shahin, K. Artificial Intelligence and Machine Learning for Sustainable Manufacturing: Current Trends and Future Prospects. *Intell. Sustain. Manuf.* **2025**, *2*, 10002. [CrossRef]
10. Rani, S.; Karnati, R.; Patel, V.; Ranganathaswamy, M.K.; Tomar, P.; Kataria, A.; Pal, A. AI-driven Optimization Techniques for Smart Sustainable Manufacturing in Industry 5.0 Ecosystem: A comprehensive Review. *Alex. Eng. J.* **2026**, *137*, 133–158. [CrossRef]
11. Shafiee, S. Generative AI in Manufacturing: A Literature Review of Recent Applications and Future Prospects. *Procedia CIRP* **2025**, *132*, 1–6. [CrossRef]
12. Huma, S.; Khan, N.; Falahat, M.; Qureshi, M.I. Generative AI for Sustainable Product Design: A Technology Convergence Framework Integrating Multi-Objective Optimisation and Smart Manufacturing. *IET Collab. Intell. Manuf.* **2026**, *8*, e70051. [CrossRef]
13. Khalfallah, A.; Leitao, C. Sustainable Manufacturing and Green Processing Methods. *Machines* **2024**, *12*, 815. [CrossRef]
14. Khan, N.; Sikandar, H.; Akhtar, N.; Bunthoeun, S. Circular Economy and Clean Energy Integration in Manufacturing SMEs: A Systematic Review and Multi-level Theoretical Framework. *Next Energy* **2026**, *13*, 100831. [CrossRef]
15. Psarommatis, F.; May, G.; Azamfirei, V. Product Reuse and Repurpose in Circular Manufacturing: A Critical Review of Key Challenges, Shortcomings and Future Directions. *J. Remanuf.* **2025**, *15*, 273–310. [CrossRef]
16. Mei, W.; Cao, Z.; Zhao, X.; Wu, Q. Effect of Nozzle Parameters and Spindle Speed on the Oil Mist Penetration Mechanism in MQL High-Speed Milling of a GH4169 Alloy. *Machines* **2026**, *14*, 420. [CrossRef]
17. Namlu, R.H.; Kılıç, Z.M. Comparative Analysis of Vibration Axis Effects on Ultrasonic Vibration-Assisted Machining of Inconel 718. *Machines* **2026**, *14*, 64. [CrossRef]
18. Natarajan, E.; Ramasamy, M.; Elango, S.; Mohanraj, K.; Ang, C.K.; Khalfallah, A. Ensemble Learning-Based Metamodel for Enhanced Surface Roughness Prediction in Polymeric Machining. *Machines* **2025**, *13*, 570. [CrossRef]
19. Narváez, M.; Guamán, J.; Hidalgo, V.H.; Pérez-Sánchez, M.; Ramos, H.M. Lagrangian Simulation of Sediment Erosion in Francis Turbines Using a Computational Tool in Python Coupled with OpenFOAM. *Machines* **2025**, *13*, 725. [CrossRef]
20. Kunkera, Z.; Runje, B.; Tošanović, N.; Hadžić, N. Lean Tools Implementation Model in Shipbuilding Processes Under Conditions of Predominantly Custom Production. *Machines* **2025**, *13*, 260. [CrossRef]
21. Rojek, I.; Mikołajewski, D. Generative AI vs. Traditional Machine Learning for Energy-Efficient and Circular Manufacturing in Industry 5.0: A Life-Cycle-Based Framework for Sustainable Manufacturing. *Machines* **2026**, *14*, 1006. [CrossRef]

22. Ali, S.H.; Zhang, M.; Liu, G.; Zhao, B.; Ding, W.; Jamil, M.; Mohan, M.; Waris, H.; Khan, A.; Hussain, S. Advancing the Machinability and Tribological Characteristics of AISI 9310 Steel Using a Novel Ultrasonic Vibration-Assisted MQL Approach. *J. Manuf. Processes* **2025**, *145*, 99–115. [CrossRef]
23. Ali, S.H.; Yao, Y.; Wu, B.; Zhao, B.; Ding, W.; Jamil, M.; Khan, A.; Baig, A.; Liu, Q.; Xu, D. Recent Developments in MQL Machining of Aeronautical Materials: A Comparative Review. *Chin. J. Aeronaut.* **2025**, *38*, 102918. [CrossRef]
24. Wang, M.; Tang, H.; Wang, Y.; Chen, Y.; Yin, L. DHCEN-DTC: An ensemble learning approach for small-feature recognition in machining process classification. *J. Intell. Manuf.* **2026**, *37*, 629–645. [CrossRef]
25. Myśliwiec, P.; Kubit, A. Integrated Multiobjective Optimization of RFSSW Parameters for AA2024-T3 sing ANOVA Machine learning and NSGA II. *Sci. Rep.* **2025**, *15*, 38029. [CrossRef] [PubMed]
26. Chen, L.; Zheng, L.; Zhu, M. A Review of Intelligent Decision-Making and Planning Methods for Machining Process Routes. *Front. Mech. Eng.* **2026**, *12*, 1842661. [CrossRef]
27. Yuan, J.; Lei, Y.; Li, N.; Yang, B.; Li, X.; Chen, Z.; Han, W. A Framework for Modeling and Optimization of Mechanical Equipment Considering Maintenance Cost and Dynamic Reliability via Deep Reinforcement Learning. *Reliab. Eng. Syst. Saf.* **2025**, *264*, 111424. [CrossRef]
28. Muthusamy, M.; Sureshkumar, A.; Shanmugam, P.; Kaveri, P.R.; Mohamed, M.Y.N.; Sridhar, S. TinyML with CTGAN based smart industry power load usage prediction with original and synthetic data visualization towards industry 5.0. *Sci. Rep.* **2025**, *15*, 41712. [CrossRef] [PubMed]
29. Li, C.H.; Ding, W.F.; Li, B.K. Challenges and Applications of Sustainable Manufacturing Technology in Carbon Reduction. *Adv. Manuf.* **2026**, *14*, 1–3. [CrossRef]
30. Harris, M.; Wu, H. Implementing Circular Economy Principles in Micro Heat Sink Development: A Techno-Economic-Sustainability Analysis. *J. Clean. Prod.* **2025**, *527*, 146731. [CrossRef]
31. Nwagwu, C.C.; Ogorodnyk, O.; Sølvsberg, E.; Eleftheriadis, R.J.; Meskers, C. Integrating Artificial Intelligence into Life Cycle Assessment: A Framework for Balancing Automation and Human Expertise. *J. Sustain. Metall.* **2025**, *11*, 3590–3605. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.